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Decoupling Carbon Emissions from Economic Growth in China: A Cluster-Based Analysis of Provincial Trajectories and Drivers

Tianyue Xue

Reading Academy, Nanjing University of Information Science and Technology, Nanjing, China
18061201933@163.com

Abstract. Addressing global climate change necessitates decoupling carbon emissions from economic growth, a critical challenge for China as the world's largest emitter. This study examines the decoupling trajectories across China's 31 provinces from 2000 to 2023, utilizing K-means clustering, the Tapio decoupling model, and an extended STIRPAT framework. Results reveal significant regional heterogeneity: efficiency-oriented eastern provinces achieve strong decoupling through technological advances and structural upgrading; transition-pressure central and western regions show weak or unstable decoupling; while resource-dependent areas remain locked in expansive coupling due to coal-reliant industries. Key drivers include economic scale, population, and industrial structure, with effects varying across clusters. The findings underscore the need for spatially differentiated policies to support China's low-carbon transition, striking a balance between green growth and regional realities.

Keywords: Carbon Emission, Decoupling Analysis, Tapio Model, STIRPAT Model

1. Introduction

In recent years, the issue of global climate change has become increasingly prominent, with carbon emissions being a major source of greenhouse gases. As the world's largest carbon emitter, China faces the significant challenge of decoupling its economic growth from carbon emissions. Although national goals for green development and a low-carbon economy have been set, such as those emphasized in the 14th Five-Year Plan to promote high-quality growth and achieve carbon peaking and neutrality [1,2], regional development disparities have led to considerable differences in the decoupling progress across provinces. Existing research has explored the decoupling of carbon emissions from economic growth at the national level [3], but few studies have delved into provincial variations and the regional dynamics behind them, particularly the challenges faced by resource-dependent and industry-intensive regions [4]. Most literature focuses on the role of green innovation in developed areas, lacking a systematic comparison of decoupling levels and driving mechanisms across different regions. Therefore, this study aims to address this gap by examining the decoupling status of carbon emissions from economic growth and its driving mechanisms across

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different types of provinces in China, in order to provide a scientific basis for formulating region-specific low-carbon development strategies.

2. Methodology

2.1. Study area

This study selected China's 31 provinces (excluding the Hong Kong and Macao Special Administrative Regions and Taiwan Province) as the research area.

Despite China's rapid economic expansion, this growth remains uneven across regions. Figure 1 illustrates the developmental disparities among provinces within the study area. By taking the median values of each province's carbon emissions and GDP in 2000, the 31 provinces were grouped into four categories. Eastern coastal provinces, such as Guangdong, Jiangsu, and Zhejiang, achieved industrial upgrading and service sector expansion earlier, while many central and western provinces remain reliant on energy-intensive industries and resource extraction. These structural differences have led to significant variations in carbon emission trajectories and economic performance across provinces.

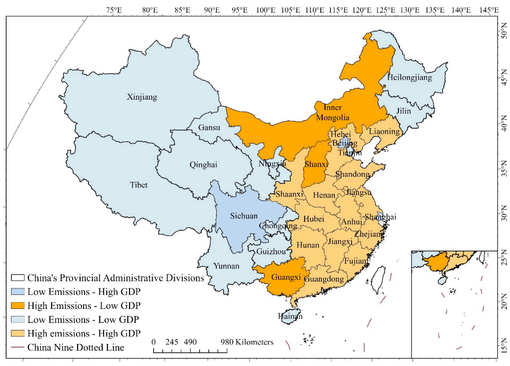

Figure 1. Economic development and carbon emissions in the study area (2000)

2.2. Data sources

This study utilizes provincial-level carbon emission data from China's 31 provinces spanning 2000–2023, sourced from the Emissions Database for Global Atmospheric Research (EDGAR Database, https://edgar.jrc.ec.europa.eu/) developed by the European Commission's Joint Research Centre (JRC). This database utilizes IPCC unified methodologies and international statistical data to provide comprehensive emission accounting results at both national and high-resolution grid scales.

Furthermore, to systematically investigate the driving mechanisms of provincial carbon emissions in China, this study constructs an extended STIRPAT model across five dimensions: population size, economic development, urbanization process, industrial structure, and energy structure. This model comprehensively evaluates the impact of each factor on carbon emissions. All relevant indicator data for the above drivers are sourced from the China Statistical Yearbook (https://www.stats.gov.cn/sj/ndsj/), using the same research regions and time periods as those for carbon emission data.

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2.3. K-means cluster

This study employs the K-means clustering algorithm to group sample data, thereby uncovering the inherent cluster structure within the dataset. K-means is an unsupervised clustering algorithm that maximizes similarity within clusters while minimizing similarity between different clusters. This is achieved by minimizing the Within-Cluster Sum of Squares (WCSS), defined as:

$$\mathrm{J} = \sum_{j=1}^{k} \sum_{x \epsilon C_j} ||x - \mu_j||^2 \tag{1}$$

Here, k denotes the number of clusters, C_j represents the set of points in the jth cluster, x is a point within a cluster, μ_j is the center of the jth cluster, and $||x - \mu_j||^2$ is the Euclidean distance from point x to cluster center μ_j .

The K-means algorithm requires the number of clusters k to be specified beforehand. To objectively determine the optimal k value for the data, this study employs the elbow rule for analysis. By computing and plotting elbow curves for k $\in$ [1,8], ultimately selecting k=3 as the optimal number of clusters.

2.4. Tapio decoupling model

The Tapio decoupling model is employed to examine the relationship between carbon emissions and economic growth by measuring the elasticity of environmental pressure relative to economic development. Following Tapio [5], the decoupling elasticity index is defined as:

$$\mathrm{e} = \frac{\% \Delta E}{\% \Delta GDP} \tag{2}$$

where E denotes carbon emissions and GDP represents economic output. Based on the value and sign of the elasticity coefficient, the carbon–economic relationship can be classified into four distinct decoupling states: strong decoupling, weak decoupling, expansive coupling, and negative decoupling. In this study, the Tapio model is applied to China’s 31 provincial-level regions from 2000 to 2023 to identify temporal and spatial heterogeneity in decoupling performance under rapid economic growth.

2.5. STIRPAT model

To further investigate the driving factors behind carbon emissions and to quantify their elastic effects, the STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model is adopted [6]. The model extends the traditional IPAT framework into a stochastic and empirically testable form. Its log-linear specification is expressed as:

$$\ln I = a + b \ln P + c \ln A + d \ln T + \varepsilon \tag{3}$$

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where I represents carbon emissions, P denotes population size, A reflects affluence measured by GDP, T captures technological and structural factors, a is a constant term, and ε is the error term. In this study, the technical level (T) is showed by energy structure. Urbanization level (U) and industrial structure (S) are considered to measure the processes of urbanization and industrialization

$$\ln I = a + b\ln P + c\ln A + d\ln T + e\ln U + f\ln S + \varepsilon \tag{4}$$

The log-transformed specification allows the estimated coefficients to be directly interpreted as elasticities, indicating the percentage change in carbon emissions resulting from a 1% change in each explanatory variable. This model provides a robust statistical framework for identifying the determinants of provincial carbon emissions, complementing the descriptive insights obtained from the Tapio decoupling analysis.

3. Results and analysis

3.1. K-means cluster result

Figure 2 displays the classification results of the K-means clustering algorithm. Based on the selected optimal k value, China's 31 provinces were clustered according to their 2023 per capita carbon emissions, per capita GDP, carbon emission intensity, and urbanization rate. Provinces exhibiting similar levels of economic development, emission intensity, and urbanization progress were grouped.

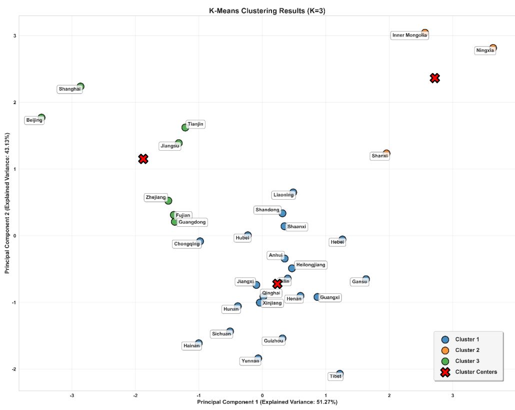

Figure 2. K-means cluster result

The clustering results reveal significant disparities in economic development levels, energy efficiency, and spatial distribution (Figure 3). Overall, the clustering pattern aligns closely with China's long-standing east-central-west regional development gradient, indicating that carbon emission characteristics are closely linked to economic geography.

Cluster 1 (Transition–Pressure Regions) is the largest group, spanning central, western, and parts of northeastern China. These provinces generally exhibit moderate economic development and medium-to-low carbon emissions, with industrialization and urbanization remaining key drivers of emission growth.

Cluster 2 (Resource-Dependent High-Carbon Regions) includes Inner Mongolia, Ningxia, and Shanxi. Located mainly in northern energy-rich zones, these areas show very high carbon intensity

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and per capita emissions, reflecting a development model heavily reliant on coal and heavy industry.

Cluster 3 (Efficiency-Oriented Low-Carbon Regions) is concentrated in eastern coastal areas and major city clusters, such as the Yangtze River Delta and Pearl River Delta. These provinces achieve higher GDP per capita and urbanization alongside lower carbon intensity, demonstrating advanced capabilities in technology and industrial upgrading.

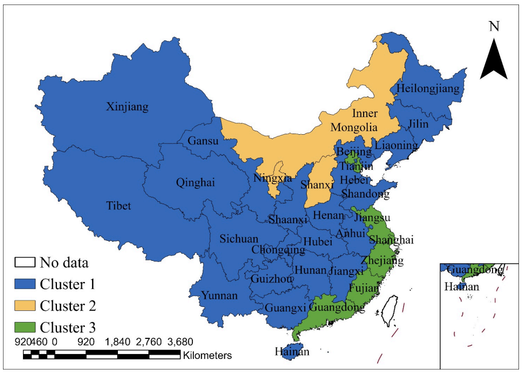

Figure 3. Cluster result distribution map

3.2. Evolution trends of economic development and carbon emissions

Figures 4 and 5 illustrate the trends in carbon emissions and GDP for the three clusters from 2000 to 2023. While economic output has grown steadily across all regions, their carbon emission trajectories reveal marked divergence—a core finding of this analysis.

Cluster 2 (Resource-Dependent High-Carbon Regions) exhibits the most rapid and persistent growth in emissions, underscoring the carbon lock-in effect of its development model. In contrast, Cluster 3 (Efficiency-Oriented Low-Carbon Regions) has achieved significant economic expansion, accompanied by a notably slower rise in emissions, reflecting higher carbon efficiency. Cluster 1 (Transition–Pressure Regions), representing the broad central and western areas, shows an intermediate pathway: emissions increased steadily before plateauing in recent years, indicating initial yet constrained progress in decoupling.

Notably, the disparity in emission growth rates among clusters has widened over time, even as GDP continued to increase. This growing differentiation in carbon trajectories highlights the uneven pace of low-carbon transition across regional development models, providing a key empirical basis for analyzing decoupling drivers and formulating differentiated policies.

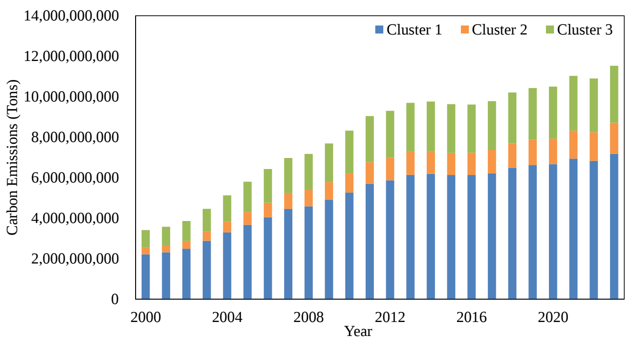

Figure 4. Annual carbon emissions changes for three clusters, 2000–2023

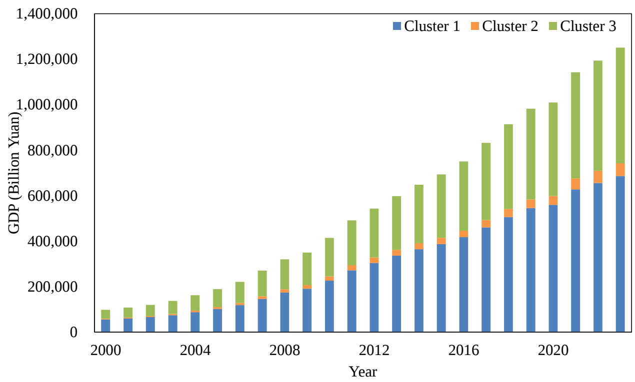

Figure 5. Annual GDP changes for three clusters, 2000–2023

3.3. Tapio decoupling result

Based on the Tapio decoupling model, the decoupling status of carbon emissions and economic growth across China's 31 provinces from 2000 to 2023 is measured, with results presented in Figure 6. A three-year cycle is adopted for phased provincial decoupling analysis, which involves calculating the Tapio decoupling index and assessing each province's decoupling performance across multiple cycles. Overall decoupling status can be categorized into weak decoupling, expansive coupling, expansive negative decoupling, and strong decoupling.

From the perspective of spatial distribution, provincial decoupling patterns exhibit distinct regional differentiation: eastern provinces lead, central and western regions are catching up, while resource-based areas lag behind. Economically advanced eastern provinces such as Shanghai, Beijing, Guangdong, and Zhejiang consistently led in decoupling optimization throughout the study period, maintaining strong or weak decoupling since 2012. These regions capitalize on advantages in high-end manufacturing and modern service clusters, while investing heavily in low-carbon technology. By sustaining high-quality economic growth while decelerating carbon emissions, they serve as national benchmarks for decoupling transformation.

Non-resource-based provinces in central and western China, such as Sichuan, Yunnan, Hunan, and Anhui, exhibit a stable and improving trend in decoupling from resource-based economies. From 2000 to 2007, expansionary coupling and weak decoupling were predominant, with the proportion of weak decoupling steadily increasing after 2008. Since 2012, provinces demonstrating strong decoupling have begun to emerge (Sichuan, Hunan). Despite having relatively weak industrial foundations, these provinces have avoided the large-scale agglomeration of heavy and chemical industries by leveraging their distinctive agriculture, light industry, and regional services. Benefiting from green development policies under the Western Development Strategy, they have progressively advanced energy structure cleanliness, narrowing the decoupling gap with eastern provinces. However, constrained by technological capabilities and capital investment, the stability of strong decoupling remains to be enhanced.

Resource-based provinces, such as Inner Mongolia, Shanxi, Ningxia, and Heilongjiang, have consistently lagged in their efforts to decouple. From 2000 to 2015, they primarily exhibited expansive coupling and weak decoupling. Although the proportion of weak decoupling significantly increased after 2016, these regions still lack provinces with strong decoupling. In some years, they even experienced negative expansive coupling. These provinces heavily rely on resource extraction and primary processing of coal, oil, and other resources for economic development, facing path dependency constraints in industrial restructuring. Although decoupling has improved in recent

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years under green development policies, the gap with other regions remains significant. These areas represent key focal points for national decoupling transformation efforts moving forward.

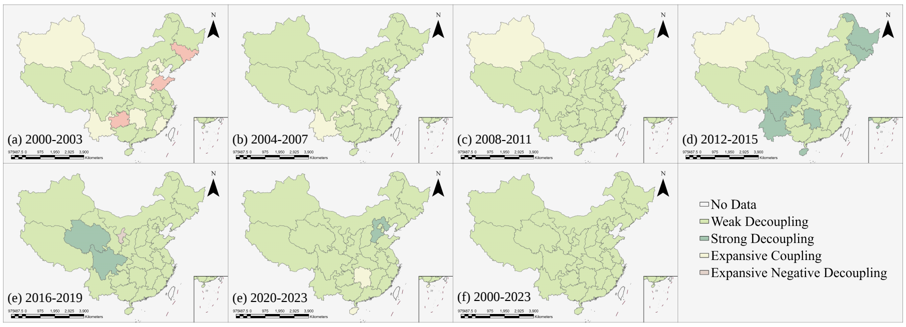

Figure 6. Spatial distribution of decoupling states

3.4. STIRPAT regression result

Within the STIRPAT framework, variables such as population size, economic development, energy structure, urbanization level, and industrial structure often exhibit strong correlations with one another. The direct application of traditional least squares estimation may lead to unstable parameter estimates and reduced explanatory power. To mitigate multicollinearity issues and enhance the robustness of estimation results, this study employs ridge regression to estimate the STIRPAT model.

Table 1 reports regression results based on the STIRPAT model, revealing significant differences in carbon emission drivers across distinct clustering regions. Overall, economic development (lnA) and population size (lnP) emerge as the primary drivers of carbon emissions, exhibiting significant positive effects across all clusters. This suggests that economic expansion and population growth continue to be key forces driving carbon emissions. However, the intensity of these factors' effects exhibits pronounced heterogeneity across different development types, reflecting regional disparities in development patterns and industrial structures.

For Cluster 1 (Transition–Pressure Regions), economic development (lnA) exhibits the highest elasticity coefficient for carbon emissions, indicating that economic growth in these areas remains highly dependent on energy consumption and carbon-intensive activities. Population size (lnP) and secondary industry share (lnS) also exerted significant positive impacts, indicating that industrial activities remain major sources of emissions. In contrast, energy structure (lnT) and urbanization rate (lnU) showed relatively weaker effects, reflecting that these regions have yet to achieve significant emission reductions through energy transition and improved urbanization quality. Overall, they remain in a transitional phase where growth is accompanied by pressure on emissions. Based on Tapio decoupling results, the relationship between carbon emissions and economic growth in this category of regions exhibits weak decoupling or expansive coupling. This indicates that despite economic growth, the increase in carbon emissions has not slowed significantly, or has only slowed for a short period.

In Cluster 2 (Resource-Dependent High-Carbon Regions), the promotional effects of population (lnP) and economic development (lnA) on carbon emissions are particularly pronounced, while the energy structure (lnT) also exhibits a significant positive impact. This indicates that an energy structure dominated by coal and heavy chemical industries significantly amplifies carbon emission growth. Moreover, the positive impact of secondary industry share (lnS) further confirms the path dependence of resource-based regions toward high-carbon industries. In contrast, the influence of

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urbanization rate (lnU) is insignificant, suggesting that urbanization advancement has not effectively alleviated carbon emission pressures and may instead be offset by high-carbon industrial structures.

For Cluster 3 (Efficiency-Oriented Low-Carbon Regions), economic development (lnA) and population (lnP) remain key drivers of carbon emission growth, but their elasticity coefficients are relatively low, reflecting higher economic efficiency and technological sophistication. The positive impact of energy structure (lnT) and secondary industry share (lnS) on carbon emissions remains significant, though their coefficients are markedly smaller than in resource-based regions. This indicates that industrial upgrading and service sector development have partially mitigated the emissions-driving effect of industrial expansion. Notably, urbanization rates (lnU) exhibit a negative impact in these regions. Although not entirely significant, this suggests that high-quality urbanization, intensive development, and technological agglomeration hold potential advantages in reducing emissions per unit. According to Tapio decoupling results, carbon emissions and economic growth in these regions exhibit strong or weak decoupling. This is particularly evident in efficiency-driven regions along the southeast coast, where economic growth is largely achieved without relying on significant increases in carbon emissions.

Table 1. Ridge regression results of carbon emissions driving factors for each cluster

Variable	Cluster 1	Cluster 2	Cluster 3
Constant	0	0.001	0
lnA	0.8769***	0.6192***	0.6340***
lnP	0.3969***	0.6688***	0.4430***
lnT	0.1894***	0.0129	0.1315***
lnU	-0.0108	-0.2214***	-0.0468
lnS	0.2917***	-0.0299*	0.2566***
R^2	0.8818	0.9886	0.9516
F	743.0878	1142.7297	637.3425
Sig. (F)	0	0	0

Note: *, **, and *** represent significance levels of 1%, 5%, and 10%, respectively.

The ridge regression results in Table 1 demonstrate highly significant model fit across all clusters. To further validate the model's generalization capability, we employed leave-one-out cross-validation (LOOCV) for evaluation. As shown in Figure 7, the root mean square error (RMSE) and mean absolute percentage error (MAPE) for all clubs remained low, with bias (Bias) is close to zero, and the coefficient of determination (R^2) is high. This indicates that the model exhibits small prediction errors, high accuracy, and no obvious systematic bias, and can effectively fit different subsets of data. Additionally, the model passed robustness tests and residual diagnostics, further validating its stability and accuracy.

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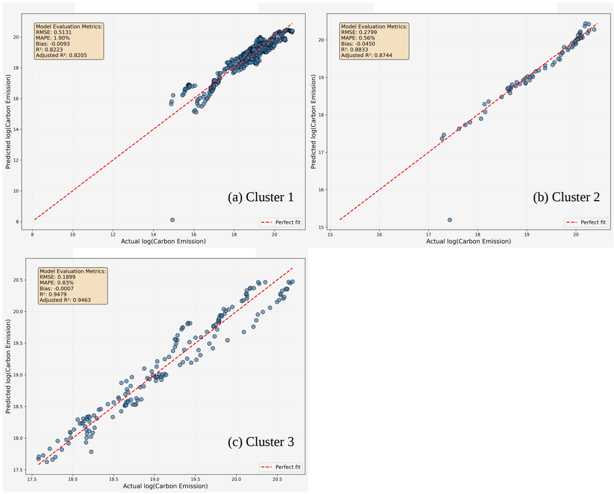

Figure 7. Logarithmic scatter plot of measured vs. estimated carbon emissions for each cluster based on LOOCV

4. Discussion

4.1. Comparison with previous studies

The findings of this study align with and extend the existing literature on regional carbon decoupling in China. The results confirm established patterns, such as the stronger decoupling observed in advanced eastern regions like Guangdong and Zhejiang. This outcome is attributed to technological innovation and industrial upgrading, which is consistent with the conclusions of Hu et al. [7] and Xia et al. [8]. However, significant divergences are also revealed.

A key point of contention concerns the potential for decoupling in resource-dependent regions. Contrary to the findings of Xiong, Deng, and Ding [9], who argued that provinces like Inner Mongolia have achieved decoupling through energy efficiency gains, the analysis of Cluster 2 shows persistent and strong coupling between economic growth and emissions. This discrepancy is critically explained by the Jevons Paradox [10]. In these regions, efficiency improvements in coal-intensive sectors lower the cost of energy use. This can stimulate further industrial expansion and increase total consumption, thereby offsetting the benefits of carbon reduction. Such a rebound effect is supported by Wang, Liu, and Tan [11].

Furthermore, while studies such as Wu et al. [12] correctly identify the structural challenges in industrial regions, the diagnostic analysis in this study highlights a state of coupling incoherence in Cluster 1. There, despite policy efforts and some efficiency gains, decoupling remains weak or inconsistent. This is because economic growth remains tightly linked to carbon-intensive industrial output and coal-based energy systems. This suggests that technology alone is insufficient without deeper industrial restructuring, a nuance less emphasized in prior work. Therefore, this study provides a more nuanced understanding of the drivers of decoupling. It highlights that regional pathways are not uniform and that structural factors can significantly limit the effectiveness of standard policy tools.

4.2. Regional development dynamics and strategic implications

The findings of this study reveal the diverse regional development dynamics in China, presenting different challenges and opportunities for implementing sustainable development policies. The fact

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that Cluster 3 (Efficiency-Oriented Low-Carbon Regions) is already achieving significant decoupling suggests that green growth is feasible in economically advanced regions. The shift towards service-based economies, advanced manufacturing, and clean technologies in these areas aligns with ecological modernization theory, which posits that economic growth can be achieved without significant environmental degradation if technological innovation is leveraged appropriately. For these regions, policies that promote technological innovation, such as subsidies for clean technology and investments in green infrastructure, should be prioritized.

However, for Cluster 2 (Resource-Dependent High-Carbon Regions), where economic activities are heavily reliant on high-carbon industries, degrowth strategies may need to be considered. Studies such as those by Jackson argue that degrowth strategies, which focus on reducing production and consumption levels to achieve sustainability, may be necessary in these regions to truly curb emissions. This does not imply economic stagnation but rather a structural transformation towards less resource-intensive sectors. Strategic implications for these regions could include policies aimed at diversifying the economy, reducing reliance on fossil fuels, and investing in energy transition technologies. For instance, Inner Mongolia could benefit from investments in renewable energy industries, such as wind or solar power, which would help reduce the carbon intensity of its economy.

For Cluster 1, achieving relative decoupling from carbon emissions requires not only technological advancements but also a structural shift in the economy. Focusing on energy efficiency, low-carbon technologies, and the development of clean energy infrastructure will be crucial for achieving this goal. Moreover, industrial transformation, combined with smart urbanization and policies encouraging green growth, can provide a viable pathway for achieving sustainable development in these regions. By diversifying their economic base and reducing reliance on high-carbon industries, these regions can foster more sustainable growth while minimizing their environmental footprint.

4.3. Limitations and future prospects

This study has some limitations that must be acknowledged. First, regional data quality might vary, particularly in the case of more remote or less economically developed provinces. Additionally, while this study offers a detailed analysis of decoupling dynamics at the provincial level, further research should include sectoral analyses to examine how different industries contribute to regional emissions, particularly in resource-intensive sectors. Moreover, the STIRPAT model is sensitive to model specification, and while the use of ridge regression helped mitigate multicollinearity, more robust models incorporating additional factors could offer even deeper insights.

Future research should explore longitudinal trends in carbon emission decoupling and test the effectiveness of specific policy interventions in regions like Cluster 2, where decoupling has been less pronounced. Moreover, research could investigate the potential role of global trade dynamics, particularly in regions that heavily rely on exports, and how trade policies may impact the relationship between carbon emissions and economic growth.

5. Conclusion

This study has systematically evaluated the decoupling of carbon emissions from economic growth across China's 31 provinces, revealing significant spatial and temporal heterogeneity. The key finding is that the national trend towards weak decoupling masks a three-tiered reality: Cluster 3 (Efficiency-Oriented Low-Carbon Regions) is at the forefront of strong decoupling, Cluster 1

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(Transition–Pressure Regions) exhibits inconsistent progress, and Cluster 2 (Resource-Dependent High-Carbon Regions) faces persistent challenges with expansive coupling. The STIRPAT model further clarified that while economic scale and population are universal drivers, their elasticities and the role of industrial structure, energy mix, and urbanization differ profoundly across these clusters, necessitating distinct policy pathways.

This analysis is subject to certain limitations. The provincial emissions data, while authoritative, are estimated and may not fully align with local inventories. The K-means clustering provides a clear but static snapshot, unable to capture dynamic provincial transitions between categories over time. Furthermore, despite its robustness, the STIRPAT framework may not fully capture the influence of institutional quality or specific innovation policies.

Ultimately, the research underscores that achieving China's dual carbon goals is not a one-size-fits-all endeavor. Success hinges on implementing spatially differentiated strategies that carefully blend the tools of green growth with the transformative insights of post-growth thinking, tailored to the specific socio-economic and ecological realities of each region.

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